Predictability and calibration beyond the medium range

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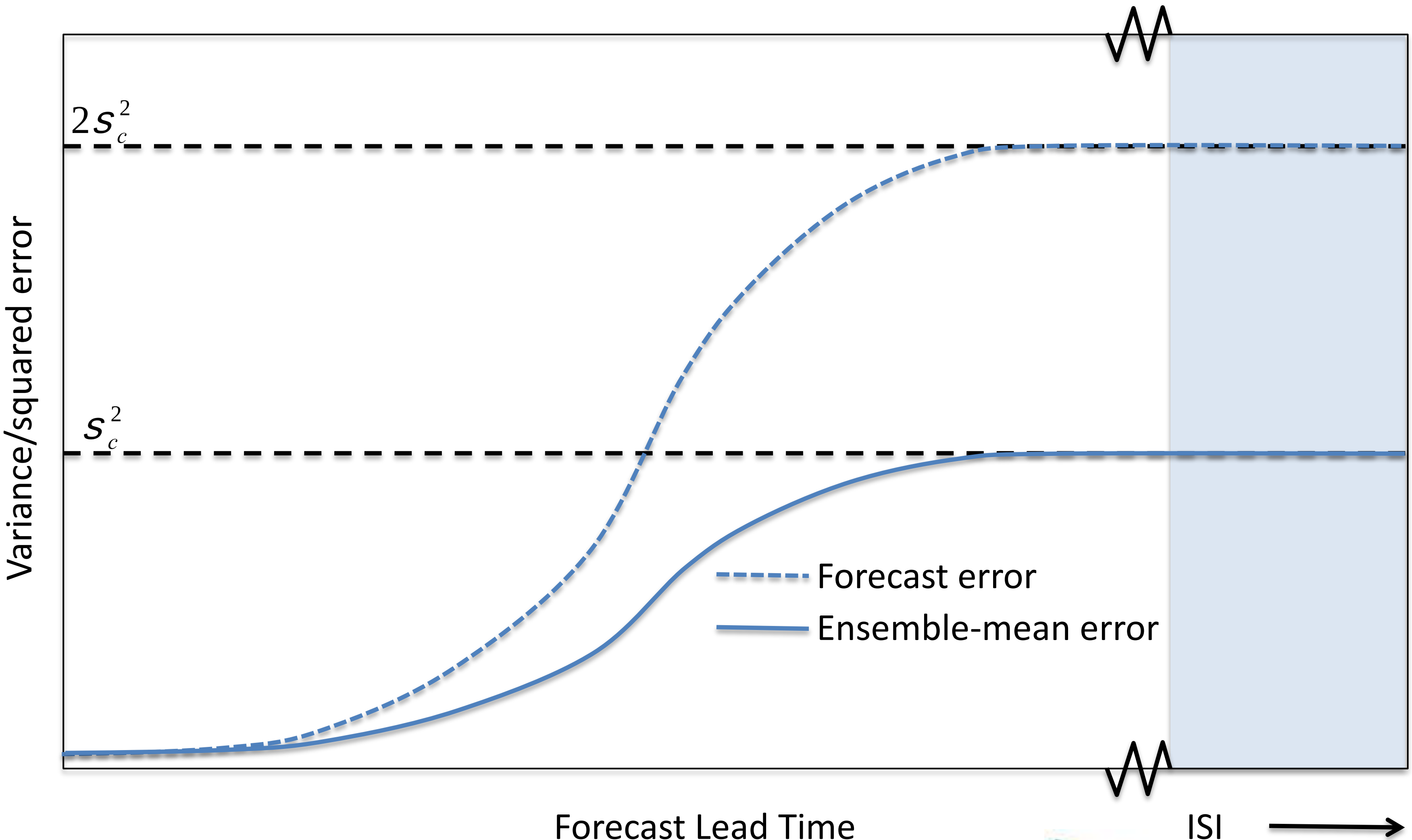
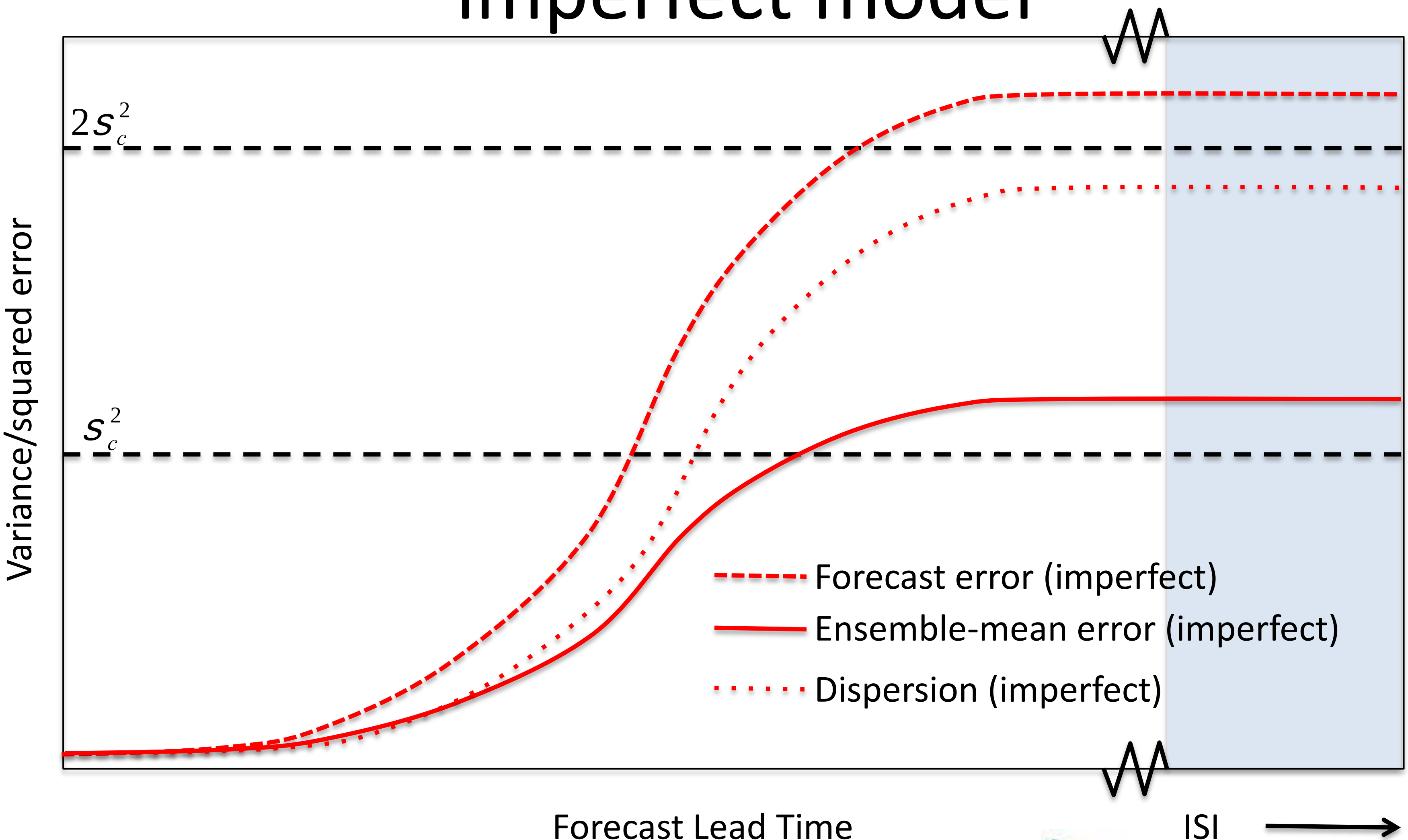
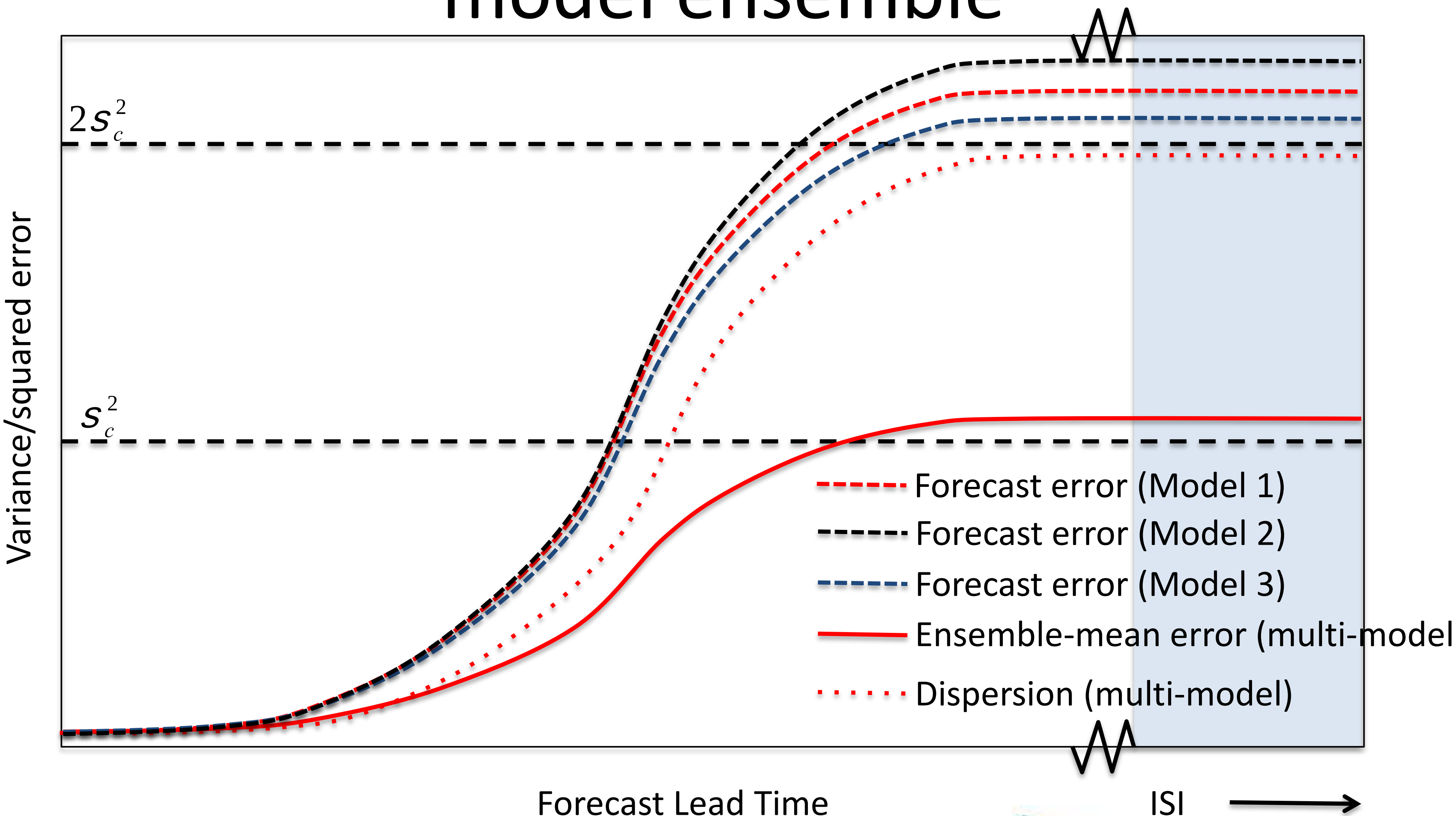
Predictability at ISI time scales: perfect model and perfect ensemble



Predictability at ISI time scales: imperfect model



Predictability at ISI time scales: multi-model ensemble

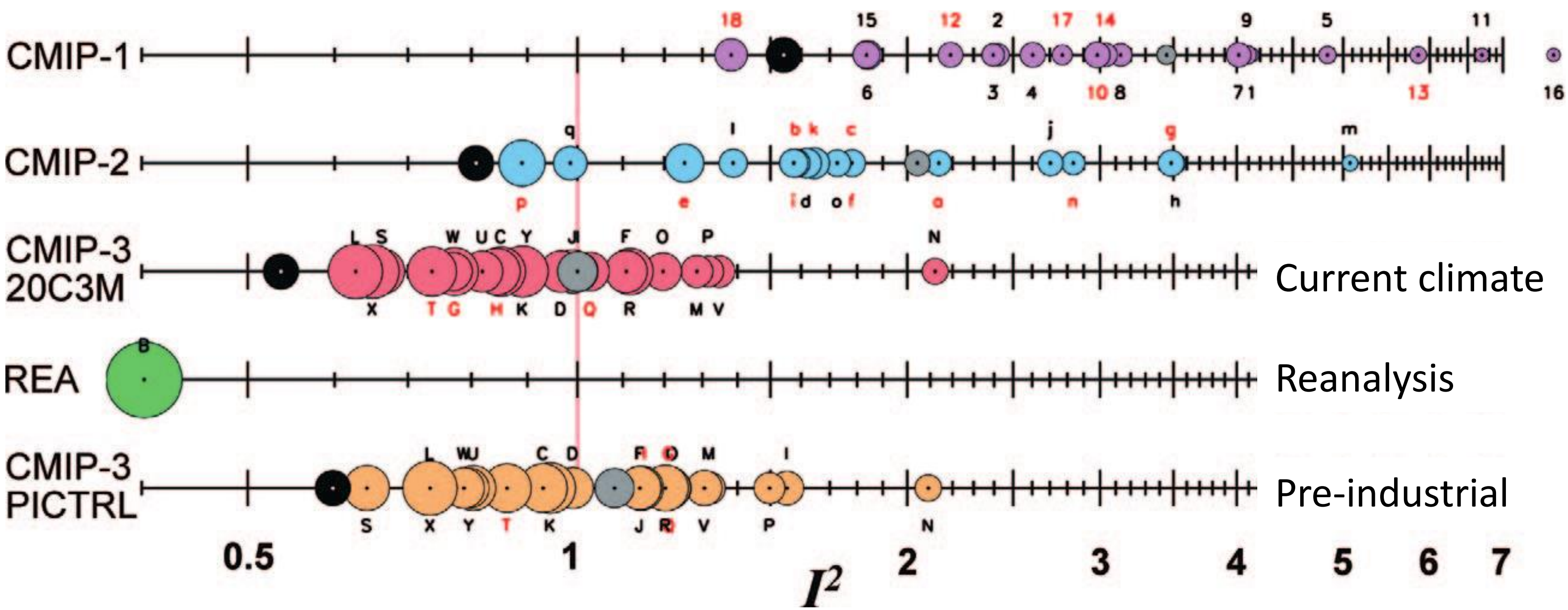


Notes/Questions

- ISI time scales are beyond deterministic and probabilistic error saturation for weather
- Expect saturation of ensemble mean error to be lower when:
  - multi-model spatially varying biases cancel
  - apparently random model errors cancel each other

- Is spread meaningful in very slow (predictable) modes, or are we just dealing with slowly varying model errors that cancel?

Model inter-comparisons



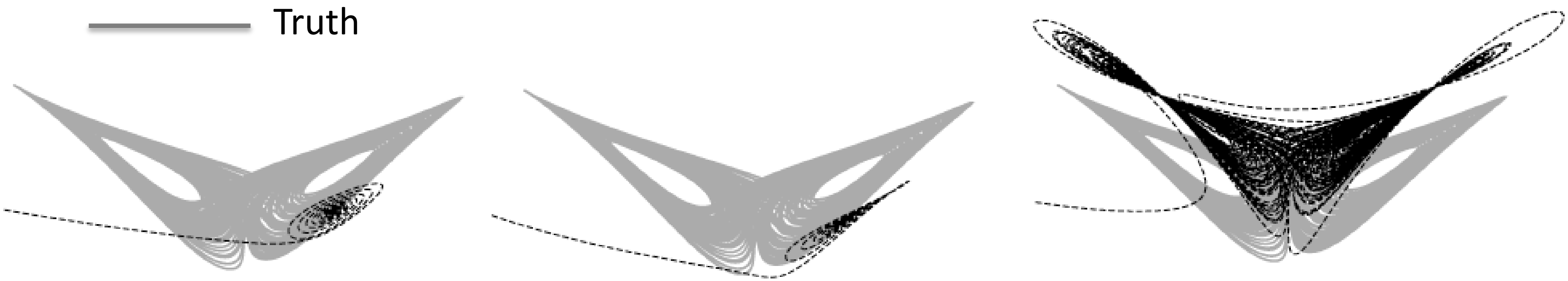
From Reichler, Thomas, Junsu Kim, 2008: How Well Do Coupled Models Simulate Today's Climate?. *Bull. Amer. Meteor. Soc.*, **89**, 303–311. doi: http://dx.doi.org/10.1175/BAMS-89-3-303

Multi-model ensemble mean: why does it usually improve skill?

- Model forecasts have conditional errors that appear random, and are evenly distributed about the observations
- Each model's systematic errors also cancel out systematically

Answer is still a bit unclear. Does it matter?

Different attractor structures

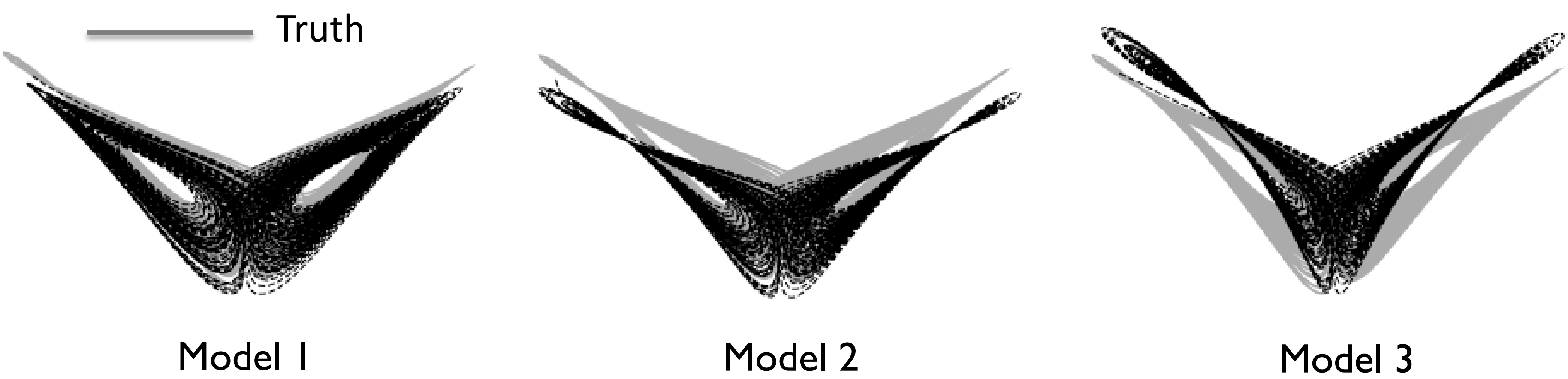


Model 1: fixed point   Model 2: fixed point   Model 3: strange attractor

- Same Lorenz 1963 system with different parameter values can substantially alter the dynamics
- Exchange information amongst the models by nudging each model toward the others; tune coefficients by minimizing the ensemble mean squared error

Plots courtesy Frank Selten, KNMI, and the SUMO project

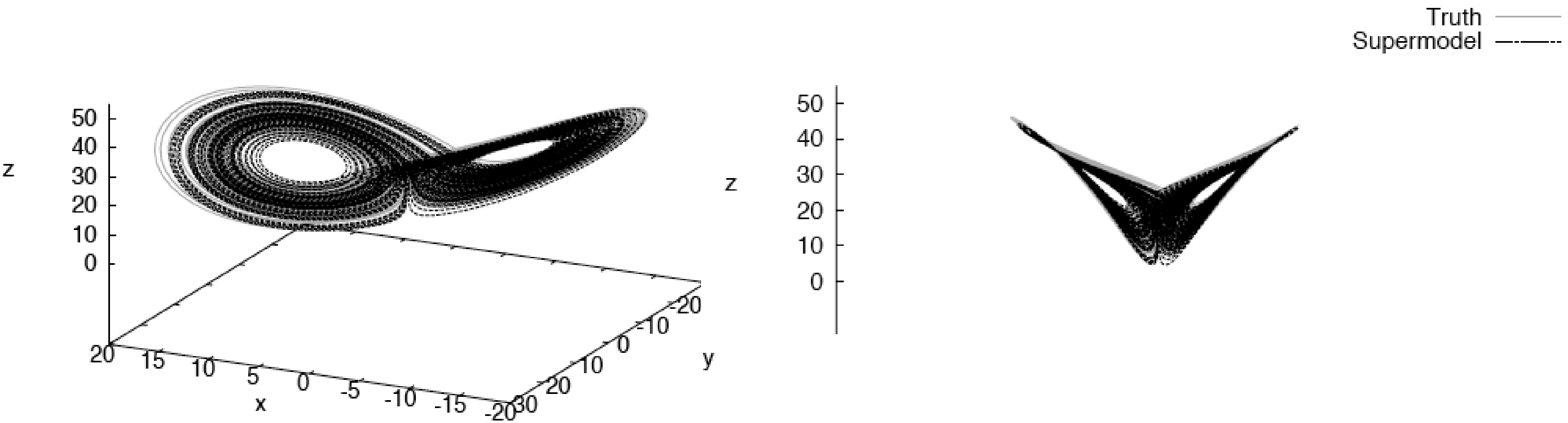
Coupled models: displaced attractors



- Fixed-point attractors are nudged to chaotic motion
- Attractors remain systematically biased and on opposite sides from the truth

Plots courtesy Frank Selten, KNMI, and the SUMO project

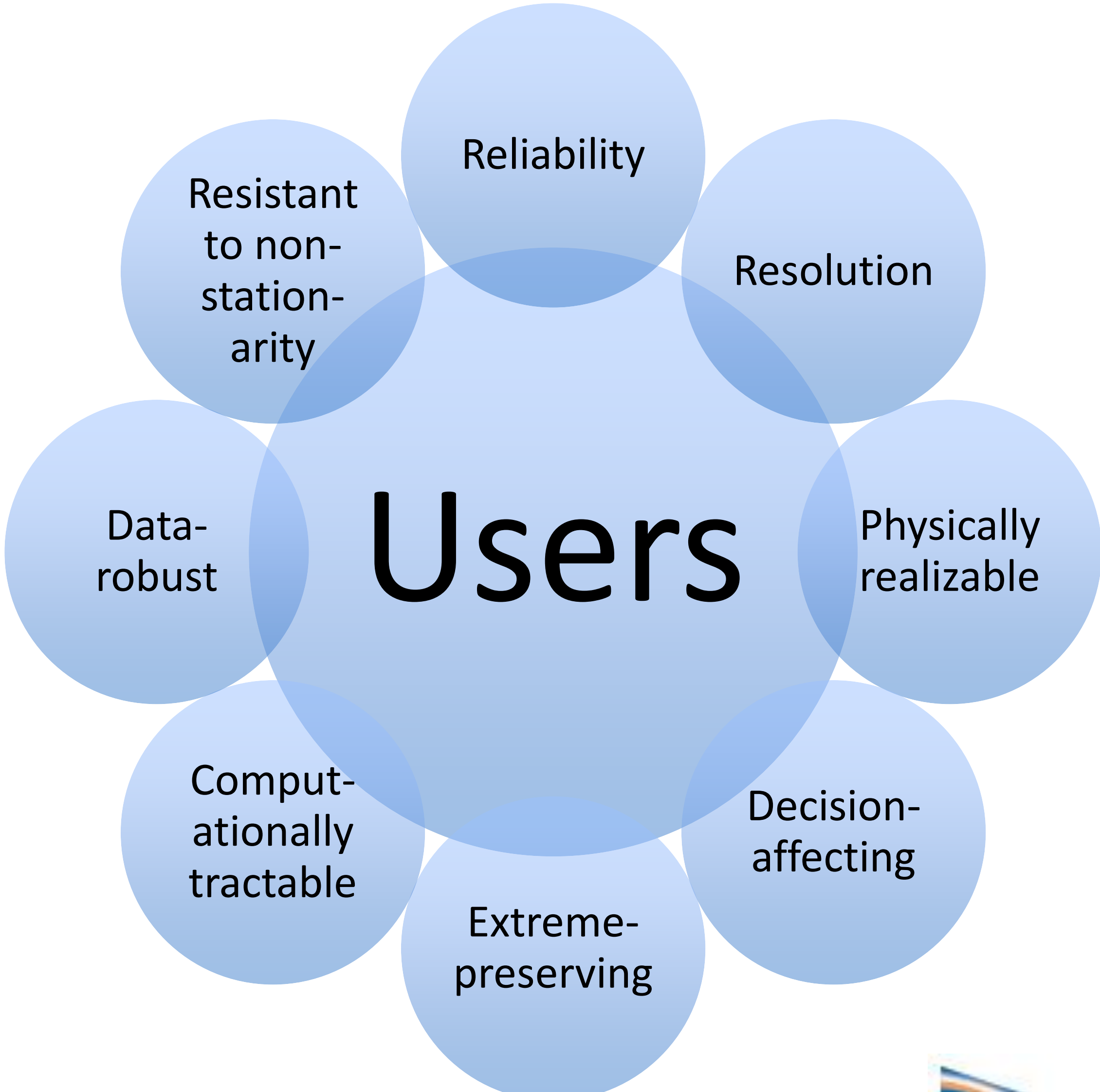
Combination of nudged models



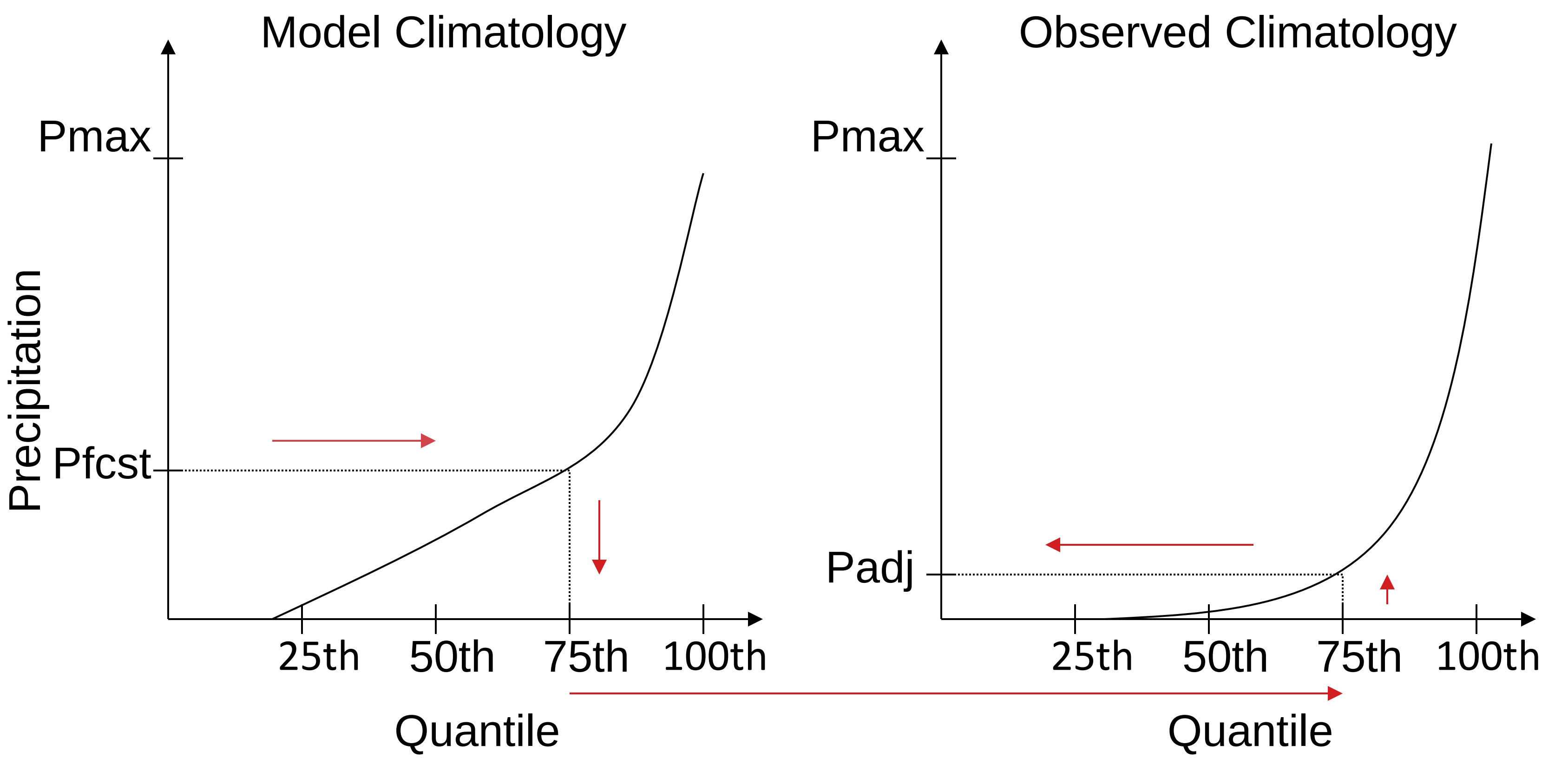
- Resulting ensemble mean is negligibly different from the truth.
- Can be thought of as a calibration.

Plots courtesy Frank Selten, KNMI, and the SUMO project

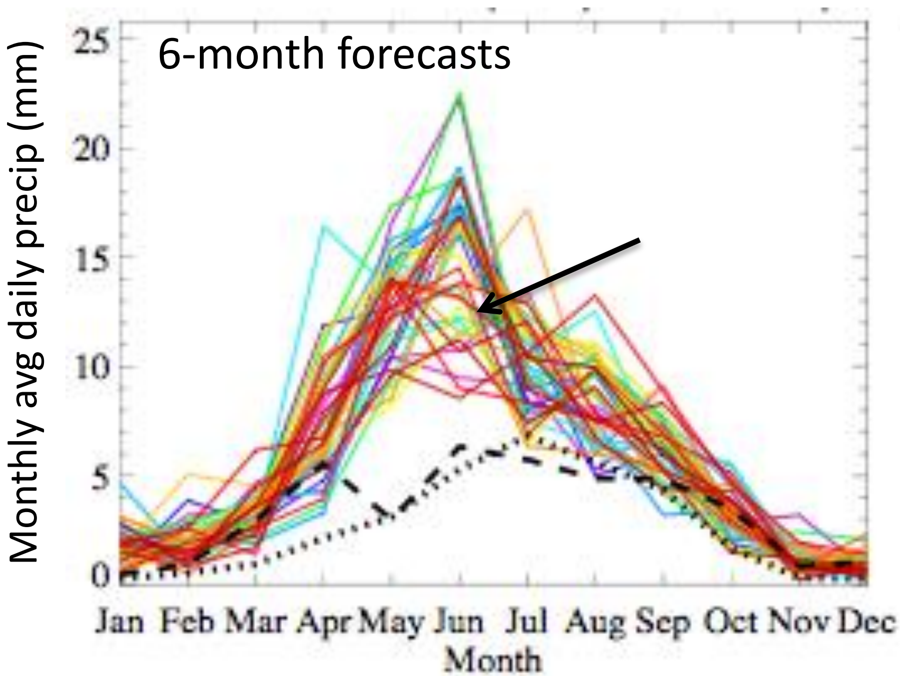
Calibration requirements

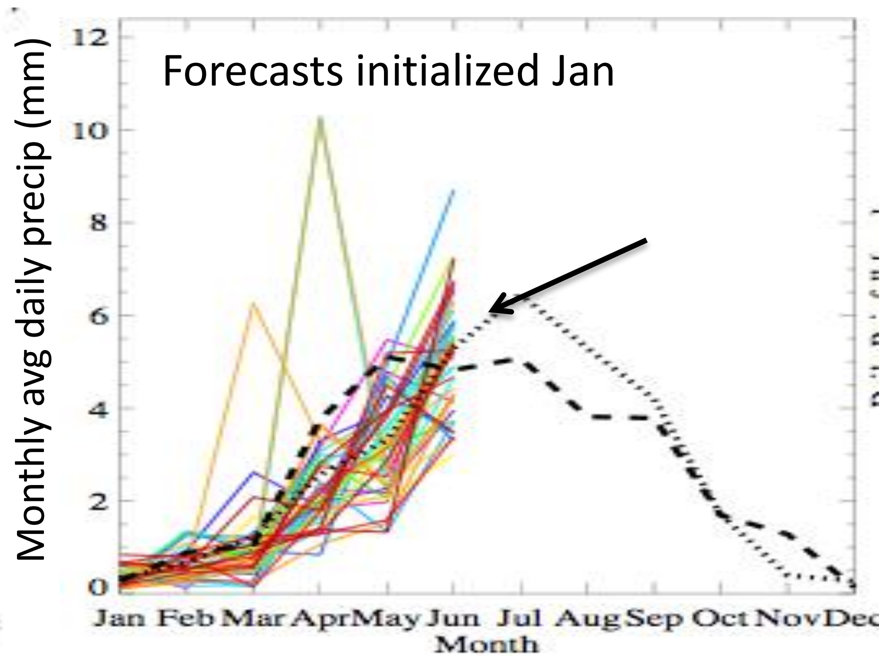


A common approach: quantile mapping



Monthly-avg precip forecasts

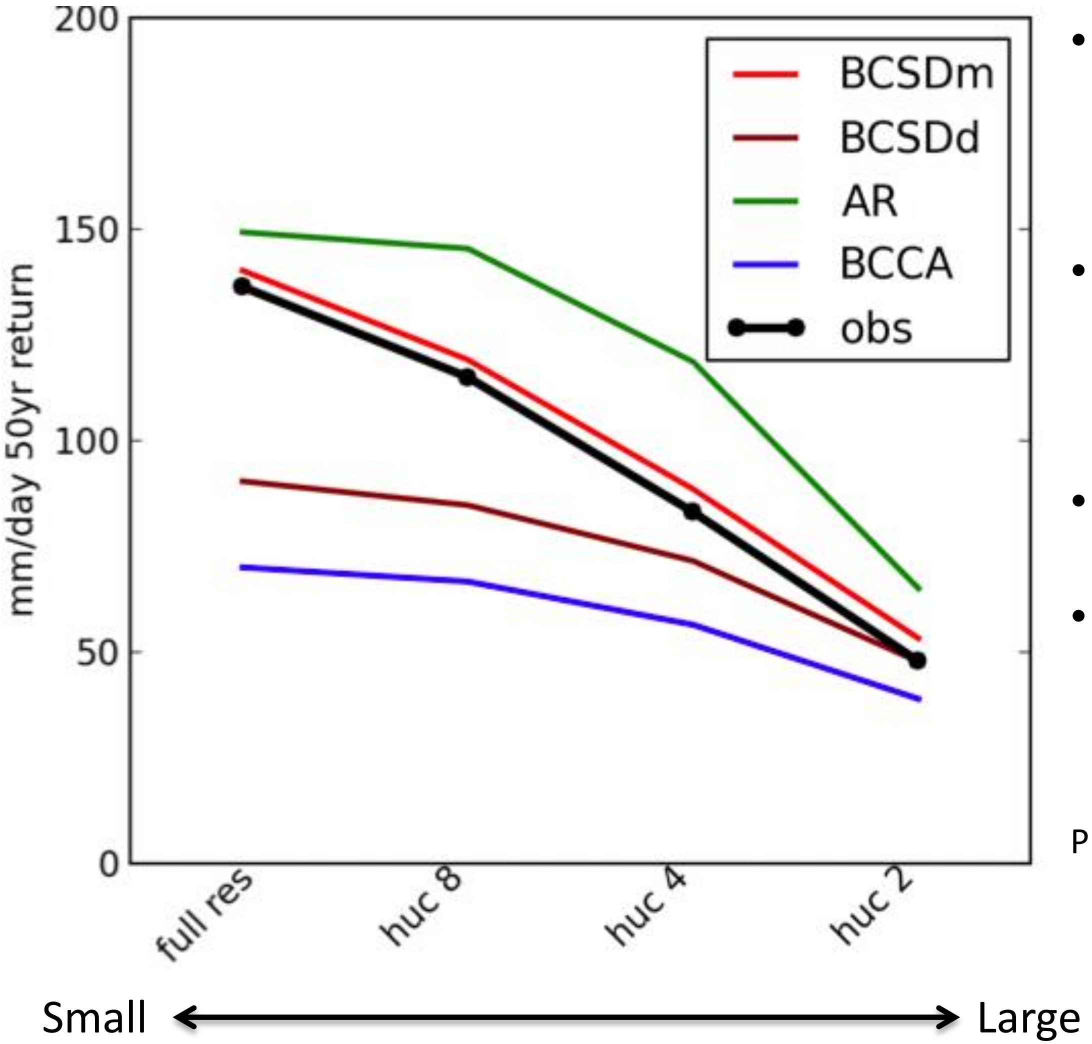




- ECMWF ensemble forecasts for 2003 for a river basin in Bangledesh
- Quantile mapping improves forecasts compared to obs (dashed)
- Forecast error bounded by climatology (dotted)
- [Note] quantile mapping by grid point can preserve some of the spatial and temporal correlations in a forecast model

Plots courtesy Tom Hopson, NCAR

Extreme monthly average precip



- All methods here except AR have quantile regression as part of the procedure (AR regression is similar)
- Extreme events generally not preserved under downscaling/calibration, but it is possible (BCSDm)
- Scale response depends on details of method
- Should we leave calibration to the particular user?

Plot courtesy Ethan Gutmann (NCAR).

Presenting forecasts to users (some thoughts)

- Giving a user only calibrated forecasts eliminates/minimizes his ability to drive model improvement.
- We want to know from users what aspect of a model forecast is important for their decision process.
- Need to put actual forecasts in front of people. Let them interact with the data. Track where they go. Indicates both trust and utility.